The overlap between criminals and victims of crime

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Disclaimer #1

These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/.

Disclaimer #2

- Sensitive research area
  - Victim blaming
    - Esp. domestic violence, sex crimes
- We aim to better understand the behavioral patterns that put victims and offenders into contact, not to blame

Motivation

- Criminals are more likely to become victims (and vice-versa)
  - Long history in criminological and sociological studies (Von Hentig, 1948; Wolfgang, 1958).
  - Less studied in economics (Deadman and MacDonald, 2004; Entorf, 2013)
- Shaffer (2004)
  - Offenders are 1.5 – 7 times more likely than non-offenders to be victims
  - Victims are 2 – 7 times more likely than non-victims to be offenders

Motivation

- NZ Police, 2014 - 2019:

Table 1. Bivariate frequency counts of any victimization and any offending, 2014-2019

		victim		
		no	yes	total
offender	no	6,216,300	183,200	6,399,500
	yes	413,800	74,200	488,000
	total	6,630,100	257,400	6,887,500

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2019. Counts have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol.

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Motivation

- NZ Police, 2014 - 2019:

Table 2. Probability of victimization conditional on offending history, 2014-2019

		victim		
		no	yes	total
offender	no	.9714	.0286	1.000
	yes	.8480	.1520	1.000
	total	.9291	.0719	1.000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2019. Frequencies are based on counts that have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol.

Motivation

- Conditional probabilities:

$$\Pr(\text{Victim} = 1 \mid \text{Offender} = 0) = .029$$

$$\Pr(\text{Victim} = 1 \mid \text{Offender} = 1) = .152$$

$$\Pr(\text{Offender} = 1 \mid \text{Victim} = 0) = .062$$

$$\Pr(\text{Offender} = 1 \mid \text{Victim} = 1) = .288$$

Research Questions

- **Is there a causal link between criminality and victimhood?**
  - **Insufficient empirical evidence to date**
- Is this a fully simultaneous relationship?
  - Existing literature suggests O → V, but not vice versa
- How can we best utilize the panel structure of our administrative data to better understand the relationship between criminality and victimhood?

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Preview of Findings

- Offending and victimization are subject to common unobserved factors
- Some predictors of joint V/O status: age (concave down), NZ born, and female
- Victimization and criminality are jointly determined
  - Suggested by results from both recursive bivariate probit and dynamic panel models with individual/time fixed effects
  - Victimization in year *t* increases by 5% when offending in year *t* occurs, and vice-versa
  - Previous victimization (offending) is a strong predictor of current year victimization (offending)

Theoretical Background

- V/O overlap: a stylized fact with various explanations…
- Routine activity/lifestyle exposure theory
  - Daily risky activity brings attractive/poorly guarded target of crime into contact with offenders (Hindelag *et al*., 1978; Cohen and Felson, 1979; Madero-Hernandez, 2019)
  - Some lifestyles increase exposure to would-be offenders
    - E.g., hanging out at a bar every night, dealing drugs, etc.
  - Economists: risk preferences

Theoretical Background

- Retaliation theory
  - "Code of the streets"
    - Topalli *et al*., 2002; Mullins *et al*., 2004; Ulmer, 2007; Taylor *et al*., 2010; Klement, 2019
  - Often associated with gang behavior and those living on "the streets"
  - Some individuals believe that some victimizations deserve a retaliatory response

Theoretical Background

- Institutional theory
  - V/O driven by incarcerated individuals who are victimized while imprisoned
    - Violent victimizations more common for those appearing vulnerable or whose traits are more antagonizing to other inmates (Ellison, Steiner, and Wright (2018)

Literature

- Many descriptives analyses of criminal behavior and victimization, but few quantitative studies on overlap
- Deadman and MacDonald (2004)
  - Youth Lifestyles Survey (UK), self reported, 4,848 subjects aged 12-30
  - Recursive bivariate probit
  - Offenders more likely to be victims, but not vice-versa
- Entorf (2013)
  - German Crime Survey, 960 individuals above 18 years of age
  - Sample meant to serve as a control group for the German Inmate Survey
  - Same findings as Deadman and MacDonald (2004)

Literature

- Ousey, Wilcox, and Fisher (2010)
  - Rural Substance Abuse and Violence Project (RSVP)
  - Followed 4,102 student in Kentucky from 7th to 10th grade (13 – 16)
  - Latent variable structural equation modelling (fully simultaneous)
  - Offenders more likely to be victims
  - After controlling for individual-level FE, previous victims are less likely to offend in the future
  - Simulation offers evidence that Arellano-Bond GMM and latent SEM models outperform pooled OLS, RE, FE

Contribution

- Only study to use a census of all investigated criminal and victimization incidents
- Previous studies lack external validity
  - Samples on teenagers, young adults, or those mimicking the demographics of prisoners
- Previous studies rely on the accuracy of self-reported measures
- The detailed nature of NZ Police data allow us to examine simultaneity of violent crime, repeat offending/victimization, IPV, family violence, thefts, etc.

Data

- New Zealand Police data, 2014 - 2019
  - Recorded Crime Offenders Statistics (RCOS)
  - Recorded Crime Victims Statistics (RCVS)
- Estimated resident population (ERP) used as the spine
  - V/O individuals not included in the ERP were excluded
- Only incidents linked to a person ID
- Only incidents that resulted in at least a warning

variable	(1) $V = 0, O = 0$	(2) $V = 0, O = 1$	(3) $V = 1, O = 0$	(4) $V = 1, O = 1$
female	.510	.515	.518	.524
age	47.22 (19.34)	48.30 (19.10)	48.17 (18.37)	48.92 (18.27)
European	.595	.618	.609	.624
Māori	.152	.163	.157	.164
Pacific Peoples	.063	.063	.061	.062
Asian	.136	.116	.131	.113
MELAA	.015	.013	.013	.012
other	.039	.027	.029	.025
born in NZ	.616	.799	.683	.839
citizenship:				
Great Britain	.035	.030	.032	.028
India	.018	.010	.016	.010
China	.023	.016	.021	.016
Australia	.014	.012	.013	.012
Europe	.020	.011	.014	.011
North America	.007	.005	.006	.005
Asia	.034	.021	.027	.018
Central and Latin America	.005	.002	.003	.002
Africa and Middle East	.009	.006	.008	.005
Pacific Islands	.018	.015	.016	.015
parent charged	.040	.042	.039	.040
parent convicted	.035	.037	.034	.035
parent prison	.003	.003	.003	.004
annual earnings	56,252 (49,803)	44,911 (34,769)	56,300 (47,047)	36,631 (31,616)
observations	1,191,300	143,600	115,300	53,500

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Empirical Model

- Two approaches:

1. We pool data and examine the relationship between any victimization and any criminal conduct over the sample period (seemingly unrelated bivariate probit):

(1) $V_i^* = \boldsymbol{X_i \beta_i} + \varepsilon_{1,i}, \quad Victim_i = 1(V_i^* > 0)$

(2) $O_i^* = \boldsymbol{X_i \beta_i} + \varepsilon_{2,i}, \quad Offender_i = 1(O_i^* > 0)$

(3) $\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]$

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- ρ is the tetrachoric correlation – a measure of correlation between two binary variables
  - An indication of simultaneity

- We also estimate recursive bivariate probit models where $V_i^* = f(O_i^*, X_i)$ and $O_i^* = f(V_i^*, X_i)$

Empirical Model

2. We utilize the panel structure of data using dynamic panel models (Arellano-Bover/Blundell-Bond GMM estimation):

(4) $V_{it} = \sum_{j=1}^{p} \alpha_j V_{i,t-j} + \beta O_{it} + \boldsymbol{X_{it}\gamma_1} + \boldsymbol{W_{it}\gamma_2} + \delta_t + \varepsilon_i + \epsilon_{it}$

for $i = 1, \dots, N$ and $t = 1, \dots, T_i$

(5) $O_{it} = \sum_{j=1}^{p} \theta_j O_{i,t-j} + \vartheta V_{it} + \boldsymbol{X_{it}\mu_1} + \boldsymbol{W_{it}\mu_2} + \pi_t + \sigma_i + \tau_{it}$

for $i = 1, \dots, N$ and $t = 1, \dots, T_i$

- Built for large N but small T_i
- Assumes no autocorrelation in the idiosyncratic errors (testable)

Empirical Model

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for $i = 1, \ldots, N$ and $t = 1, \ldots, T_i$

- Removes time invariant individual characteristics (ε_i, σ_i)
- Removes trends over time (δ_t, π_t)
- Estimates the impact of current offending (victimization) on current victimization (offending), controlling for previous behavior

Results

1. Marginal effects of SUR bivariate probit model
   - Taking 2019 ERP and using cumulative crime/offending variables
2. Marginal effects of recursive bivariate probit model
   - Taking 2019 ERP and using cumulative crime/offending variables
3. Dynamic panel results

Table 3. Marginal effects of *V = 1, O = 1* from seemingly unrelated bivariate probit model of any criminal victimization and any offending in New Zealand, 2014 - 2019

variable	*V = 1, O = 1*
female	.0009*** (.0002)
age	.0010*** (< .0001)
$age^2/100$	-.0009*** (< .0001)
Māori	.0002 (.0003)
Pacific Peoples	-.0004 (.0004)
Asian	.0007** (.0003)
MELAA	-.0012 (.0008)
other	-.0078*** (.0005)
born in NZ	.0285*** (.0002)
$\hat{\rho}$	.3854*** (.0018)
citizenship controls	YES
observations	1,503,600

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are reported. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2018. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively.

victimization and offending in New Zealand, 2019

variable	(1) $V = f(O, \mathbf{X})$	(2) $O = f(V, \mathbf{X})$
any offending since 2014	.016*** (.0001)	
any victimization since 2014		.015*** (.0007)
female	.0004*** (.0001)	.0003*** (< .0001)
age	.0004*** (< .0001)	.0003*** (< .0001)
$age^2/100$	-.0004*** (< .0001)	-.0002*** (< .0001)
Māori	.0001 (.0001)	< .0001 (< .0001)
Pacific Peoples	-.0002 (.0002)	-.0001 (.0001)
Asian	.0003** (.0001)	.0002* (.0001)
MELAA	-.0006*** (.0004)	-.0002 (.0002)
other	-.0333*** (.0003)	-.0022*** (.0003)
born in NZ	.0116*** (.0009)	.0088*** (.0011)
$\hat{\rho}$	-.052* (.031)	-.204*** (.0416)
citizenship controls	YES	YES
observations	1,503,600	1,503,600

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. The population consists of all victims and offenders investigated within

Table 10. Arellano-Bond (dynamic panel) estimation, 2014-2019

variable	(1) *Victim(t)*	(2) *Victim(t)*	(3) *Offender(t)*	(4) *Offender(t)*
Offender(*t*)	.0500***	.0479***		
	(.0031)	(.0036)		
Victim(*t-1*)	.0326***	.0396***		
	(.0044)	(.0069)		
Victim(*t-2*)		.0104**		
		(.0053)		
Victim(*t*)			.0538***	.0522***
			(.0033)	(.0040)
Offender(*t-1*)			.0744***	.1124***
			(.0048)	(.0082)
Offender(*t-2*)				.0434***
				(.0055)

Arellano-Bond test for zero autocorrelation in first-differenced errors:

order	*p*-value	*p*-value	*p*-value	*p*-value
1	.0000	.0000	.0000	.0000
2	.1521	.1734	.0002	.3841

instruments	21	20	21	20
controls	YES	YES	YES	YES
year FE	YES	YES	YES	YES
individual FE	YES	YES	YES	YES

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2019. Marginal effects are calculated at variable means. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. The null hypothesis for Arellano-Bond test is no autocorrelation.

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Conclusions

- A sensitive area…
- Should we direct more of our criminal justice resources towards this group?
  - A small percentage of the population
  - Resources may be better directed at prevention
- It may be beneficial to communicate results in a campaign designed to inform offenders and potential offenders of their likelihood of victimization given certain illegal activities
  - Becker (1968) proposes that the choice to commit a crime depends on the chance of getting caught, but what about the likelihood of being subsequently victimized?

Future Research

- Currently working out the timing issue
- With annual data there is no way of telling whether *V* comes before *O* within year *t*, for example
- We are currently transforming data into a monthly panel
  - Requires taking a 10% random sample so sample size is manageable
  - This will make the dynamic panel specification much more powerful/insightful

Future Research

- We plan to conduct sub-analyses on certain types of events:
  - Intimate partner violence
  - Offenses involving a weapon
  - Theft
  - Domestic violence
  - Violent Offenses
  - Repeat offending and victimization

  - A significant contribution to this literature

Thank You

- Thank you for your time
- Questions?
- Contact:
  - christopher.erwin@aut.ac.nz